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ML-RECON SIMULATION MODEL: A MONTE CARLO PLANNING AID FOR MAGIC LANTERN

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The U.S. Navy currently has no means to conduct sea mine reconnaissance with assets that are organic to Aircraft Carrier Battle Groups or Amphibious Ready Groups. Magic Lanten is an Airborne Laser Mine Detection System (ALMDS) under development, that is designed to search for floating and shallow moored mines using a helicopter-mounted laser-optic sensor. It is the only ALMDS operationally tested by the Navy to date.

This thesis develops a Monte Carlo simulation model called ML-Recon, which is intended for use as a tool to plan mine reconnaissance searches using the Magic Lantern system. By entering fundamental initial planning information, the user can determine the number of uniformly-spaced tracks to fly with a Magic Lantern-equipped helicopter to achieve a certain level of assurance that the area contains no floating or shallow moored mines. By employing Monte Carlo methods, ML-Recon models the three primary stochastic processes that take place during a typical search: the location of the mines, the cross-track error of the helicopter, and the detection/non-detection process of the sensor.

By running ML-Recon, the user is given performance statistics for many replications of the search plan that he chooses. This approach is unique in that it provides the user with information indicating how much worse than the mean performance his plan *may* perform. ML-Recon also gives the user an opportunity to view an animation of his plan, which he can use to look for tendencies in the plan to contain holes, or *holidays*.

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ML-RECON SIMULATION MODEL:
A MONTE CARLO PLANNING AID FOR MAGIC LANTERN

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ABSTRACT

The U. S. Navy currently has no means to conduct sea mine reconnaissance with assets that are organic to Aircraft Carrier Battle Groups or Amphibious Ready Groups. Magic Lantern is an Airborne Laser Mine Detection System (ALMDS) under development, that is designed to search for floating and shallow moored mines using a helicopter-mounted laser-optic sensor. It is the only ALMDS operationally tested by the Navy to date.

This thesis develops a Monte Carlo simulation model called ML-Recon, which is intended for use as a tool to plan mine reconnaissance searches using the Magic Lantern system. By entering fundamental initial planning information, the user can determine the number of uniformly-spaced tracks to fly with a Magic Lantern-equipped helicopter to achieve a certain level of assurance that the area contains no floating or shallow moored mines. By employing Monte Carlo methods, ML-Recon models the three primary stochastic processes that take place during a typical search: the location of the mines, the cross-track error of the helicopter, and the detection/non-detection process of the sensor.

By running ML-Recon, the user is given performance statistics for many replications of the search plan that he chooses. This approach is unique in that it provides the user with information indicating how much worse than the mean performance his plan *may* perform . ML-Recon also gives the user an opportunity to view an animation of his plan, which he can use to look for tendencies in the plan to contain holes, or holidays.

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EXECUTIVE SUMMARY

The U.S. Navy currently has no mine-hunting asset organic to Aircraft Carrier Battle Groups (CVBGs) or Amphibious Ready Groups (ARGs). Mine Countermeasures (MCM) planners agree that, to conduct adequate sea mine reconnaissance, a combination of systems, each specializing in searching a different depth layer, is required to carry out adequate mine reconnaissance for a battle group transiting through potentially mined waters. A number of systems are currently under development, one of which is the Airborne Laser Mine Detection System (ALMDS).

ALMDS is a laser-optic mine-hunting sensor mounted on a helicopter that would give CVBGs the capability to search for floating and shallow moored mines if it were adapted to the Navy's current Light Airborne Multi-Purpose System (LAMPS) helicopter, the SH-60. Of the ALMDS systems being considered, Magic Lantern, a system developed by Kaman Corporation, is the only one that has undergone operational tests by the Navy.

The simulation model developed in this thesis, ML-Recon, was built as an interactive computer planning tool for the employment of Magic Lantern. It models the stochastic processes that take place during a typical search, and provides the planner with a realistic estimate of the expected performance of his plan. The following steps summarize the operation of this planning tool.

1) The user is prompted to input the size of the channel intended for the search, the distance to the channel from the helicopter's base ship, the number of mines expected in the channel, and the number of replications of the search plan the user would like to run.

2) Since the sensor's probability of detection capability varies with depth, a set of four graphs is presented to the user, each of which plots Percent Coverage vs. Number of Tracks for a different depth layer. The first depth layer begins at the surface, and each subsequent one represents a deeper volume than its predecessor. From these graphs the user can estimate the number of tracks to run to achieve his desired coverage. The user would be expected to determine the number of tracks from the worst performing depth layer. Also provided is a graph with an estimate for the time required to complete the search. After examining the planning graphs, the user enters the number of tracks desired for his search plan.

3) The replications of the search plan are run, and performance statistics for each completed search are recorded. During one replication, the helicopter transits from the base ship to the channel and searches for randomly located mines by flying the specified number of tracks. The tracks are spaced uniformly. However, a random cross-track error is

imparted on the helicopter's actual flight path. As the helicopter is flying, the laser is independently emitting pulses into the water. Fuel consumption is monitored throughout the search. During each track, if a mine is determined to be within the laser's sweep width, its depth and lateral range from the helicopter are checked, and the appropriate probability of detection is applied in an attempt to detect the mine. There are twenty different probabilities of detection used in the model.

4) When all replications are complete, the user is shown four performance graphs, one for each depth layer. The graphs plot the individual performance (mines detected) of each replication and the running average for all the replications.

5) The user is offered the choice of viewing an animated version of the search, repeating the replications with a different number of tracks, or quitting the program.

Unique features of ML-Recon, not present in any operational MCM planning tool, are the randomly modeled stochastic processes and the animation. The stochastic processes include 1) the random positions of the mines in the channel for each new replication of the search plan, 2) the random navigational error applied to the helicopter's flight path, and 3) the sensor's probabilistic prosecution of each individual mine it encounters.

The value of the animation is the visual representation of the helicopter's errant flight path and the associated holes, or *holidays*, in the search plan. Since the laser trails remain on the screen, after the search is complete the planner can determine the number of mines missed because of poor sensor performance and those missed because of holidays.

For model verification, ML-Recon compares favorably with an accredited analytical MCM planning program, Uniform Coverage Plan (UCPLN). Yet, by running several replications and employing random numbers to model the stochastic processes of the search, ML-Recon provides more information to the planner about the spread of possibilities in the performance of the search plan.

I. INTRODUCTION

A. BACKGROUND

The U.S. Navy currently has no mine-hunting asset organic to Aircraft Carrier Battle Groups (CVBGs) or Amphibious Ready Groups (ARGs). Once a mine threat has been identified in a particular theater of interest, Mine Countermeasures (MCM) ships and helicopter squadrons are deployed to the area. Their arrival may take days or longer, depending on their transportation requirements and the availability of an in-theater logistics support base. In the meantime, battle groups and resupply ships in theater are at risk waiting for the arrival of the MCM assets.

A concept of operations document regarding sea mine reconnaissance and organic battle group self-protection, written by the Underwater MCM Office of the Chief of Naval Operations [Ref. 1], states that currently there is no single method for adequately conducting sea mine reconnaissance. No individual mine-hunting system can effectively search for mines from the surface down to the bottom, and below the seabed for buried mines. Therefore, a *suite* of sensors, each one focusing on a different depth layer, is required in a battle group to ensure adequate reconnaissance in the event that mines are suspected.

Among the sensors that would be included in this combination is an Airborne Laser Mine Detection System (ALMDS). An ALMDS is a helicopter-mounted electro-optic sensor designed to search for floating and shallow moored mines by emitting laser energy into the water and recording reflected energy from mine-shaped objects. The sensor contains a classification algorithm that determines whether a reflected signal is from a mine or not.

Magic Lantern, developed by Kaman Corporation, is the only ALMDS that has been operationally tested by the Navy. Two Magic Lantern sensors are presently under contract by the Navy, and others are being considered [Ref. 2]. Future systems would be mounted on Light Airborne Multi-Purpose System (LAMPS) helicopters, which are an integral part of all CVBGs and conceivably could be deployed with ARGs.

In August, 1994, the Airborne Mine Warfare Systems Program Office at the Naval Sea Systems Command sponsored operational tests of Magic Lantern in Fort Walton Beach, Florida [Ref. 3]. Data were collected during these tests by METRON, an independent scientific consulting firm, in conjunction with the Coastal Systems Station in Panama City, Florida. The data collected were analyzed to determine the sensor's capability to detect mines, a characteristic described as *probability of detection* ($\mathbf{P_d}$). The nature of modern MCM required that precise navigational data for the helicopter also be

collected during each of the mine-hunting sorties. These data reflect a navigational error between the intended track and the actual flight pattern of the helicopter.

At present, ML-Recon, the simulation described in this thesis, is the only performance model designed specifically for the Magic Lantern system. In addition, it is the only MCM planning aid that models stochastic processes with the use of random numbers. The result is that the information generated by ML-Recon gives the planner a more thorough understanding of the potential outcome of his search plan.

B. PROBLEM STATEMENT

The MCM planner or Battle Group Commander approaching potentially mined waters will have a Magic Lantern-equipped helicopter among a combination of mine-hunting sensors at his disposal. Although this asset will not neutralize or clear mines, it can provide the planner with critical reconnaissance information about the shallowest water layer of an intended transit route. If mines *are* detected, an alternate route can be chosen. If no mines are detected, and the search plan is adequately thorough, the shallowest layer can be considered sanitized, or mine-free.

Depending on the size of the channel, the search may require a very carefully chosen plan. A search plan that is too extensive may not be completed before aircrew rest or refueling and scheduled helicopter maintenance are required. A plan that is too sparse may miss mines due to holes in the search. Knowing the following information:

- channel size;
- percent sanitization desired;
- detection capability of the sensor;
- helicopter and aircrew logistic considerations;

the MCM planner needs to determine:

- the number of tracks to fly and their inter-track spacing to complete a reconnaissance search that will achieve the sanitization percentage desired, and;
- the time required to complete the search.

C. APPROACH

The approach to solving the problem is to analyze the Magic Lantern system and the data collected during operational tests, and to construct a Monte Carlo simulation model, ML-Recon, that can be used as a search planning tool.

II. THE SYSTEM

A. OVERVIEW

The Magic Lantern system consists of two main parts: the laser-optic sensor and the helicopter upon which the sensor is mounted. The helicopter used in operational tests thus far has been the SH-2 Seasprite, also manufactured by Kaman Corporation. Since the SH-2 has been superseded by the SH-60 Seahawk as the battle group LAMPS helicopter, the sensor will ultimately be used on the newer airframe [Ref. 2]. Adjustments to ML-Recon in order to conform to system updates are discussed later in the model description.

B. THE HELICOPTER

LAMPS helicopters are embarked on most cruisers, destroyers and frigates in a CVBG. These ships carry one or two helicopters and two or three crews, respectively [Ref. 5]. Refueling, as well as crew changes, can be conducted while the helicopter is on deck and still running. However, scheduled periodic maintenance prevents around-the-clock operation of a single helicopter.

For the purposes of this study a helicopter travels at two speeds: *transit speed* and *search speed*. As the names imply, transit speed refers to the velocity of the helicopter as it is in transit between the channel and its base ship. Search speed is the speed at which it conducts the search. Transit speed is greater than search speed. As helicopter speed is more a function of blade pitch than rotor speed, the ratio of time spent at transit speed to that spent at search speed does not significantly affect the frequency of refueling.

C. THE SENSOR

Aspects of the sensor that are pertinent to the analysis are the shape and structure of the search volume and the associated $\mathbf{P_d}$ characteristics. Although the sensor is mounted outside of the aircraft on the starboard side, the offset can be pre-programmed into a Global Positioning System (GPS) navigation unit, so the sensor is assumed to be at the centerline of the helicopter.

Although an optimum airspeed for the sensor's performance does exist [Ref. 3], the operation of the sensor is separate from the helicopter and, thus, independent of its speed and direction. The sensor unit emits pulses of laser energy into the water column directly below the helicopter at a constant rate. Laser energy is reflected from items in the water column and received through cameras inside the sensor unit. Each camera's shutter is set to be open during a distinct time interval, delayed from the instant the pulse is emitted. Therefore, each camera captures reflected energy from a different depth zone in the water column, corresponding to the time that the shutter is open. For example, reflections from

the shallowest depths are received by the camera that opens and closes first. Once the reflected energy returns to the sensor, contacts are classified by a detection algorithm, assigned a location, and recorded.

The sweep width of the sensor is divided into several sections, as shown in Figure 1. Laser pulses are emitted at a constant rate. One cycle of these pulses begins

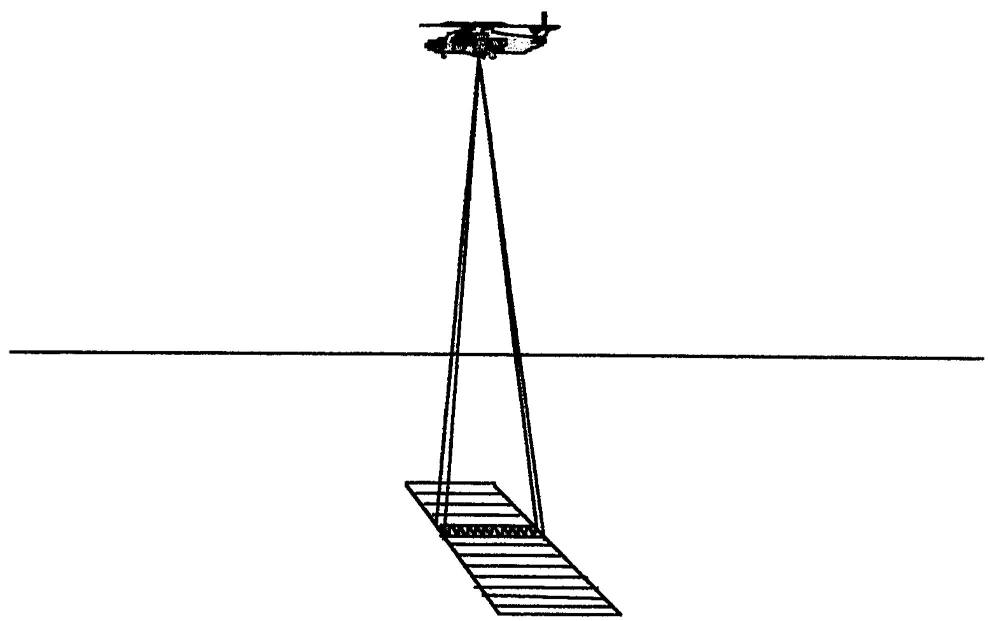


Figure 1. Magic Lantern Sensor Emitting Laser Pulse From Helicopter

at the left edge and moves through the search width to the right edge, then begins again on the left [Ref. 3]. Each pulse penetrates the water so that, at the completion of one sweep, the sensor has searched a three-dimensional space, or a *search volume*.

The $\mathbf{P}_d$ data were collected in such a way that the search volume is divided into five lateral ranges and four depth zones [Ref. 3], for a total of twenty subvolumes. Figure 2 shows the cross-section of the search volume structure (as though the helicopter were flying away from the reader) as it is described by the data. The length, width, and depth dimensions of the search volume are also depicted. The surface of the water is represented by the top line of the structure. The arrow ($\Downarrow$) in the figure shows the *nadir* position, or, the point directly below the helicopter. $\mathbf{P}_{d(1,1)}$ in the figure represents the $\mathbf{P}_d$ in the shallowest depth layer and the left-most lateral range bin.

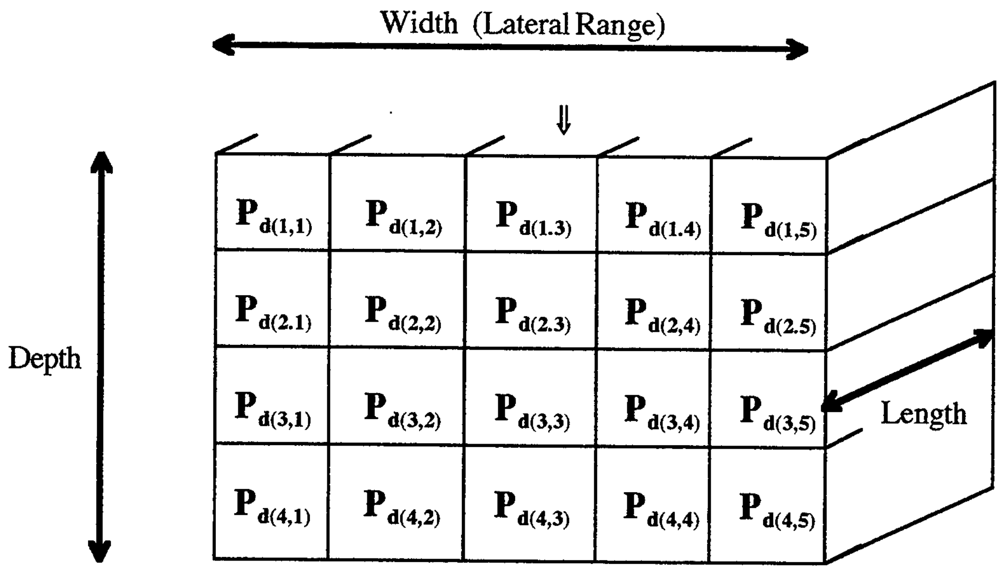


Figure 2. Search Volume Structure

The structure of the sensor's search volume reveals that a mine's depth and lateral range have an impact on whether it is detected or not. The fact that the sensor's capability varies in two dimensions (depth and lateral range) makes it unique among mine-hunting systems, and, hence, not well-represented by current planning models such as the Uniform Coverage Plan or the Non-Uniform Coverage Evaluation program, as these programs assume a single $\mathbf{P}_d$ value for the sensor used in the search [Ref. 6].

At present, this sensor has no mine-*sweeping* or clearing capability. The laser does not detonate mines intentionally or otherwise. Mines in the water that have been flown over and detected do not affect the helicopter's flight in any way. The sensor continuously emits pulses throughout the search, and the helicopter maintains a constant speed, regardless of the number of mines below or whether or not they are detected. The positions of mines that are detected are stored for future analysis by planners once the search is complete.

III. THE MODEL

A. OVERVIEW

ML-Recon is designed to simulate a helicopter with a Magic Lantern sensor executing a specific mine-hunting plan. The user is prompted to enter the size of the channel to be searched, the distance from the helicopter's base ship to the channel, the number of mines to plant in the channel, and the number of replications of the search he would like to run. Prior to selecting the number of tracks, he is given an analytical estimate of the approximate coverage he will achieve, depending on the number of tracks run. The helicopter then transits to the channel and executes the search plan. The sensor continuously emits laser pulses while the helicopter flies the specified number of tracks. At the conclusion of each search replication, detection results are recorded. When all replications have been completed, summary graphs showing the overall results are shown on the screen, and the user is offered the opportunity to see an animated version of the search.

ML-Recon is written in MODSIM II, an object-oriented, modular simulation programming language. Therefore, as aspects of the Magic Lantern system improve with more advanced technology, changes can easily be incorporated into the appropriate module of ML-Recon. Many of the parameters of the system, such as search speed, depth capability, and the various $\mathbf{P}_d$ values of the sensor, are simply entered as constants in a calculating module of the program. They can be quickly updated with system improvements. Navigational error is modeled using a normal random variable with a specific mean and variance. If a different helicopter is determined to be equipped with Magic Lantern (a very likely possibility), ML-Recon need not be rewritten. Only the new helicopter's navigational error parameters and transit speed capability are required.

In this thesis, the term *coverage* describes a percentage of water volume (a channel with length, width and depth) that has been sanitized. If a channel is 95% *covered* then, of all the mines in that channel, 95% of them are detected. From another perspective, if one mine exists in the channel, the probability that the search detects it is 0.95.

B. ANALYTICAL APPROXIMATION

The value of ML-Recon is in the stochastic processes that it models. However, since a large number of replications of the search may be rather time-consuming, the planner is provided with a graph that assists him in his initial choice for the number of tracks to run. The graph plots the expected coverage, $\mathbf{p}$, against the number of tracks flown, $\mathbf{n}$ (see Figure 3). Using the graph as a guide, the planner selects a close estimate of

the number of tracks that should be flown to achieve his desired coverage. To begin ML-Recon without any idea of the number of tracks to run would likely result in his choosing several *bracketing* trials to arrive at the ultimate number of tracks. To derive a formula for

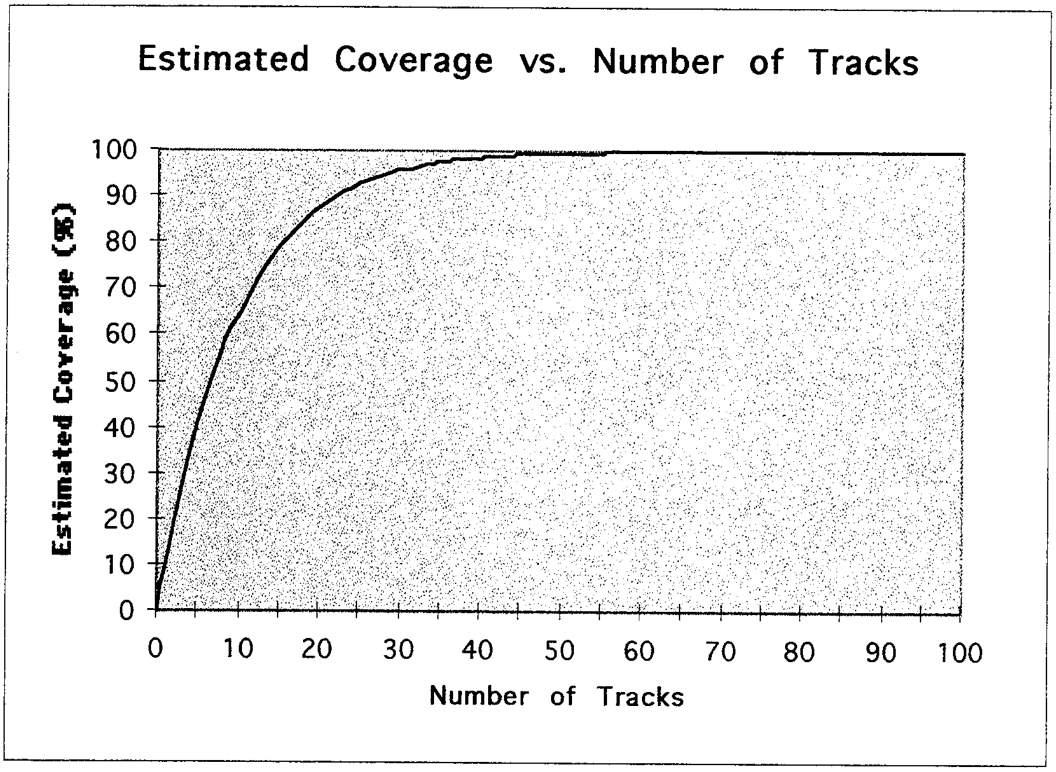


Figure 3. Analytical Estimation for Coverage

p, assume that the search width of the sensor is significantly more narrow than the width of the channel being searched. Let $\mathbf{w_a}$ be the sweep width of the sensor, which is the product of the overall search width and the $\mathbf{P_d}$, and let **a** be the width of the channel. For independent random tracks in a channel [Ref. 7], the probability that a given point is detected after **n** tracks is:

$$\mathbf{p} \equiv 1 - (1 - \mathbf{w_a}/\mathbf{a})^{\mathbf{n}} \qquad (1)$$

The parameter **a** must be entered into ML-Recon by the planner. He will generally base this number on the navigational capabilities of the ship(s) that will ultimately transit the channel once it has been deemed safe. The guidance in reference [6] for determining channel width is to use at least six times the standard deviation to navigational error of the transiting ships. The value for $\mathbf{w_a}$ is calculated by multiplying the overall search width of the sensor by its aggregate $\mathbf{P_d}$ in each depth zone. Once the replications of the actual search begin, ML-Recon uses five distinct probability of detection values across the lateral range

of the sensor (see Section C of this chapter) for each separate depth zone. The graph shows the probability that a given point in the channel is effectively searched for one through one hundred tracks. The shape of the graph indicates that there is a point at which adding more tracks achieves negligible improvement in coverage. Since the Magic Lantern system, as described, divides the water column into four depth zones and has a different aggregate $\mathbf{P}_d$ for each, four graphs are provided to the user, one for each depth zone. He would be expected to select the number of tracks required from the graph that shows the depth zone where the sensor's capability is worst.

One additional graph is provided before ML-Recon begins. This graph plots search time against the number of tracks flown (Figure 4), since time may be of critical interest to the planner. The graph shows him approximately how long his search will take. This is a

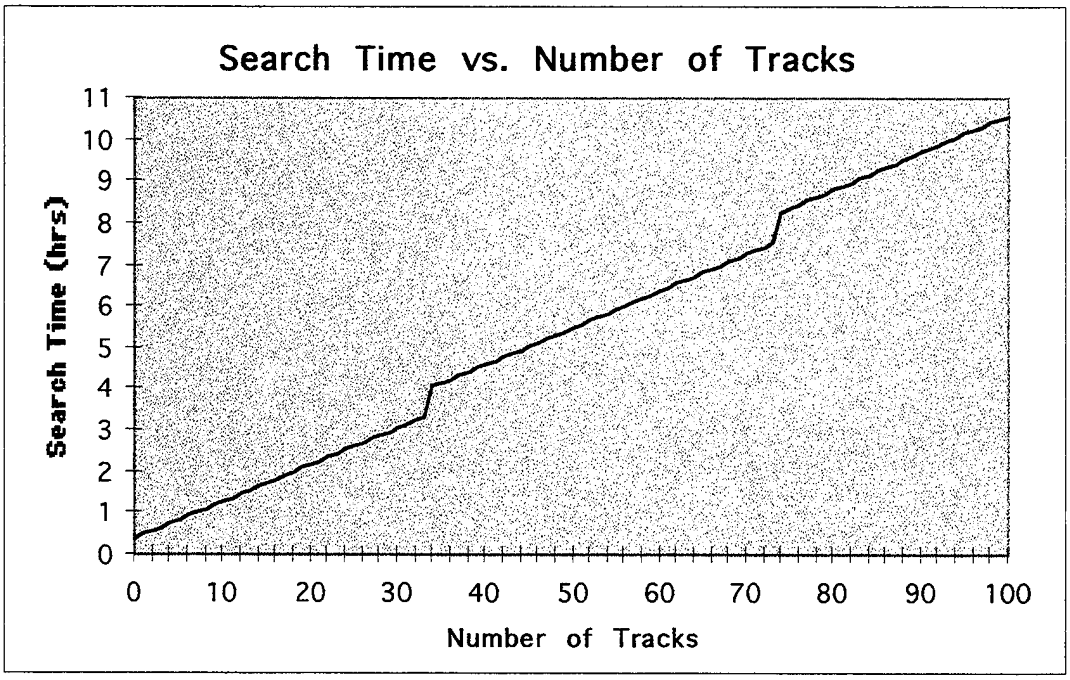


Figure 4. Estimated Search Time

piece-wise linear representation of the total distance traveled at a predetermined speed. Search time includes the time required to turn between tracks and the transit time to and from the area. The round-trip transit time can be seen on the y-axis of the graph where the number of tracks is zero. The jumps in search time occur at points where refueling is required. For searches of very long transit routes (channels), the planner may decide to break up the search into a number of shorter sections, each of which would be searched

separately. Figure 5 shows how a long channel may be divided into three shorter channels. By viewing the relationship between search time and the number of tracks

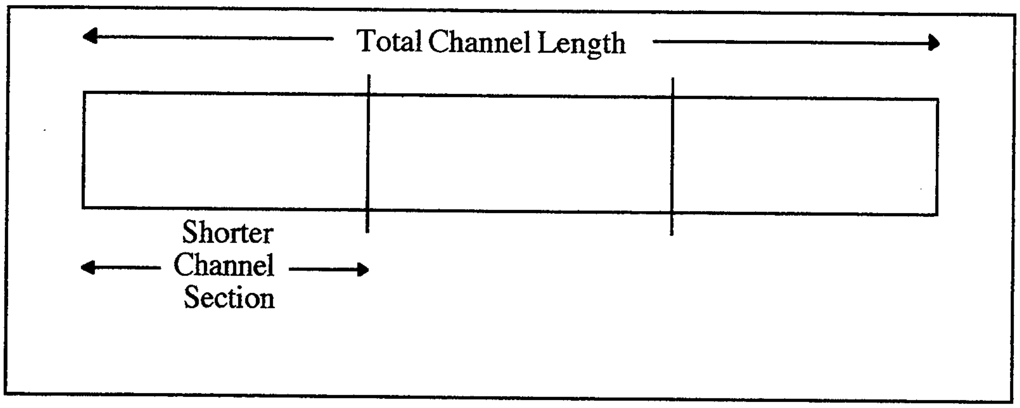


Figure 5. Long Channel Divided Into Three Shorter Sections

flown, he can modify the length of the channel sections so that a section is searched completely before the helicopter must return to its host ship for fuel.

C. STOCHASTIC PROCESSES IN ML-RECON

Three specific random phenomena are modeled. The first is the random location of mines in the channel. The second is the navigational error of the helicopter's flight path. The third is the sensor's prosecution of potential mine contacts. The two latter processes are modeled on the data that were collected during actual tests of the Magic Lantern system.

1. The Mined Channel

The channel is sized in three dimensions. The x and y dimensions are taken from the length and width entries specified by the planner at the beginning of the program. The z dimension, depth, is the maximum depth to which the sensor is capable of detecting mines. This dimension is divided into four layers to represent the four depth zones searched by the sensor.

The user is prompted to enter an estimate for the number of mines in the channel. This is done for two reasons. First, some positive number of mines in the channel is necessary in order to quantitatively assess the effectiveness of the user's proposed search plan. Secondly, although it is unlikely that the user will know the exact number of mines that are in the channel, he *may* have some idea based on intelligence information or on previously observed mine densities in the area. In such cases, he should have the ability to

apply that information rather than have the number of mines unalterably fixed for statistical convenience by a programmer who is removed from the situation at hand

Once the user enters the number of mines, that number is laid in each of the four depth zones, so that the total number of mines in the channel is actually four times the number he entered. However, since the sensor's performance in each depth zone is assessed separately, the effective number of mines in the search is the number entered by the user.

The x and y coordinates for each mine's position are determined by drawing uniform random numbers that are bounded by the dimensions of the width and length of the channel, respectively. The depth dimension is fixed, as a mine's relative depth within its depth zone is irrelevant to its vulnerability to detection. The mines remain stationary.

The size of the mines is not addressed in ML-Recon. When the tests were run on the system, the targets used were generally the same size or smaller than the typical moored mine. The data upon which the detection capability is modeled includes detection/no detection information only, since the sensor itself contains the classification algorithm for determining whether a contact is a mine or not.

2. The Helicopter Module

Although mine-hunting plans generally consist of a set of straight, uniformly-spaced tracks flown parallel to the length axis of the channel, there are a number of physical influences that prevent the helicopter pilot from flying the exact plan. If there were no error in the flight path of the helicopter, it would be flown over 100% of the channel area by choosing the number of tracks as:

$$\text{Number of Tracks} = \frac{\text{Channel Width}}{\text{Sensor Sweep Width}} \tag{2}$$

and spacing the tracks uniformly across the width of the channel, offsetting the first track by one half of a track width. However, wind gusts, inaccuracies in the tracking system onboard the helicopter, and pilot error all cause the helicopter to deviate from the intended track. The significance of this navigational error is in the resulting *holidays*, or holes, in the search plan. Figure 6 is a theoretical representation of holidays caused by navigational error in a five-track search plan. Although the error may seem exaggerated for the flight

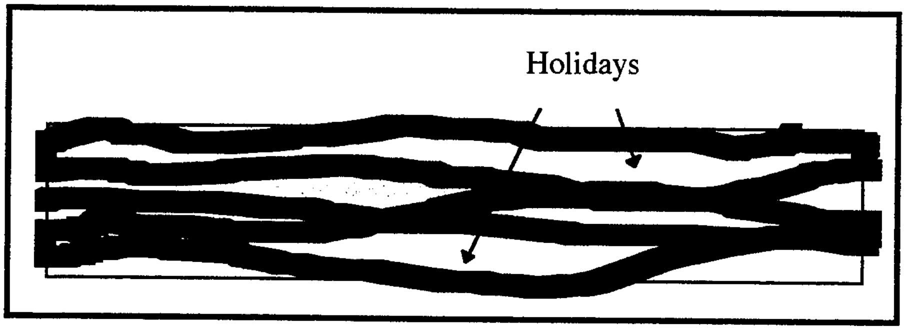


Figure 6. Holidays in a Search Plan

of a helicopter with a precise search plan, the sample of actual tracks flown during the operational tests, shown in Appendix A, indicates that such deviations are typical. [It should be noted that data such as the sample in Appendix A is only available through a position-plotting program written separately from the Magic Lantern system by an analyst at the firm that collected the data. Such information is not known to the typical Magic Lantern planner before or after the search.]

Figure 7 shows a frequency histogram of the actual position error of the helicopter from over 5000 data points. As expected, the error closely resembles a normal probability distribution. The navigational error data for the helicopter were collected once per second under various wind conditions. Wind speeds, however, were recorded only once per fifteen minute interval. At first the data were separated into *high-wind* and *low-wind* categories. The fact that there was not any difference in navigational error between the two categories may be attributable to the relatively large time interval between wind speed measurements. Since the standard deviation under both conditions was the same, no influence on the helicopter's cross-track error in ML-Recon is attributed to wind speed.

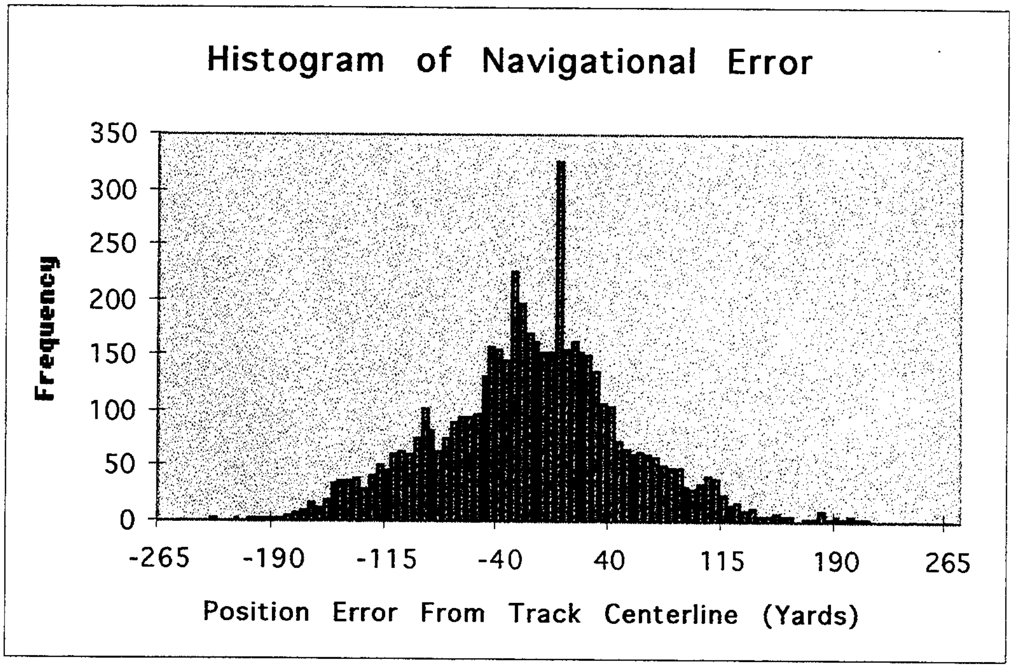


Figure 7. Histogram of Helicopter Navigational Error

To represent navigational error in the helicopter's flight path, the area searched in the model is first presented in **x-y** coordinates. The helicopter flies parallel to the **y**-axis, and its cross-track position is measured on the **x**-axis. The centerline for each planned search track (an **x** value) is calculated before the flight begins. As in real life, the ML-Recon helicopter is intended to stay directly on track for its entire length. However, to account for the factors mentioned earlier, the helicopter strays randomly to either side of the centerline. If this error were simply applied by adding a normal random number to the helicopter's lateral position at one-second intervals (the time between data points collected), the flight path would be very jagged and could tend to drift to unrealistically large distances from the centerline [Ref. 8]. By applying the smoothing process described below, a more realistic, gradually adjusting flight path is achieved.

Suppose the helicopter's lateral position error at any given time, **t**, is denoted by $\mathbf{x_t}$. At regular time intervals Δ, a new position with **x** and **y** components is assigned to the helicopter. The new **y** position is determined simply by multiplying Δ by the helicopter's speed and adding it to the previous **y** value. For the new cross-track error from centerline, $\mathbf{x_{t+\Delta}}$, first the magnitude of the previous error, $\mathbf{x_t}$, is damped by a constant, **c**, where : $0 < \mathbf{c} < 1$. This keeps the helicopter close to the track, yet does not bring it all the way back to centerline. In order to determine the value of **c**, another constant, τ, must be

extracted from the data collected during the Magic Lantern tests. Described by Washburn as a *relaxation time* [Ref. 8], τ is calculated using the equation:

$$\mathbf{c = corr(x_t,\ x_{t+\Delta}) = e^{-(\Delta/\tau)}} \tag{3}$$

The correlation coefficient for $\Delta = 10$ seconds was determined to be 0.77 from the test data. This describes the correlation between lateral position errors at ten-second intervals. By selecting a ten-second interval, sequential lateral position error measurements are close enough to be dependent on one another, but distant enough to allow the simulation to run relatively quickly. A shorter interval would require more frequent error assignments in the program and, hence, more computer processing time. Solving for τ:

$$\tau = -\Delta /\ \mathbf{ln(0.77)} \quad = \quad \mathbf{-10\ sec/\ -0.26} \quad = \quad \mathbf{38.25\ seconds} \tag{4}$$

Once τ is known, the damping constant, **c**, is calculated using equation (3). The time between instances of determining a new lateral position error is referred to as the *navigational time interval.* Since the navigational time interval for ML-Recon is also chosen to be ten seconds, the damping constant is identical to the correlation coefficient.

After the previous lateral error is damped, a random number is drawn and added to it. The random number follows a normal distribution with parameters $\mathbf{N(0,\ q)}$. The variance, **q**, is determined using the data from the tests and the damping factor, **c**:

$$\mathbf{q = s^2 - c^2s^2 = s^2(1 - c^2)} \tag{5}$$

where s is the standard deviation of the error data. Summarizing the method of assigning each new lateral position error to the helicopter:

$$\mathbf{x_{t+\Delta} = cx_t + W_t} \tag{6}$$

where $\mathbf{W \sim N(0,\ q)}$. The graph in Figure 8 illustrates the process by which the helicopter is assigned its lateral position error. Since the helicopter is assigned a new position only every ten seconds, it flies a straight line from one assigned position to the next. The sensor emits laser pulses every 0.375 seconds and requires an accurate measurement of the helicopter's position for each pulse. Therefore, a simple interpolation of the helicopter's position along the straight line between assigned positions is calculated when prompted by the sensor module.

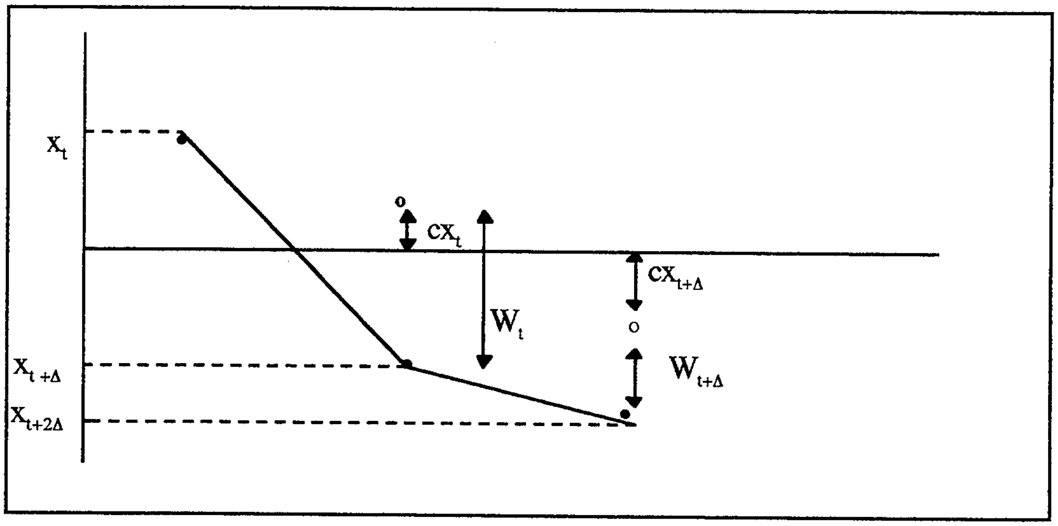


Figure 8. Helicopter Cross-Track Error Application

This process of inducing a realistic time correlation structure to smooth the helicopter's flight path is known as the Ornstein-Uhlenbeck (O-U) process [Ref. 8]. Current MCM planning tools already consider the standard deviation of navigational error [Ref. 6], but essentially with the relaxation time, τ, equal to infinity. By analyzing the error data and modeling it in ML-Recon as an O-U process, representation of the search with a realistic relaxation time is achieved.

3. The Sensor Module

The sensor module design is based on data collected during operational tests of the Magic Lantern system, but ML-Recon does not follow the exact steps carried out by the sensor. For instance, ML-Recon does not model the multiple laser pulses emitted by the sensor from one edge of the sweep width to the other. Such detail would burden the processor and result in extremely time-consuming operation of the program while adding nothing to the analysis. Rather, the sweep of the sensor through one cycle (as described in Chapter II) is considered as one event, which identifies an area with fixed length and width, referred to as the laser's *footprint*. The length of the footprint is based on the speed of the helicopter and the frequency of the pulses. More specifically, successive sweeps are modeled so that the leading edge of the previous footprint is adjacent to the trailing edge of the current one, given that the helicopter maintains a constant speed. Therefore, there is no overlap between footprints of the same track. The width of the footprint is based on the cumulative width of a cycle of pulses.

The time between sweeps in ML-Recon (0.375 seconds) reflects the frequency of the actual laser, but takes into account the lateral consolidation of the laser pulses into one footprint. Since there is no overlap from one footprint to the next in the same track, a mine can only be illuminated by the sensor once per track.

As the helicopter travels along each track, the discrete, independent steps of ML-Recon's sensor are described as follows:

- Every 0.375 seconds, the sensor emits one large, rectangular pulse that penetrates from the water's surface through all four depth zones. The x-y coordinates for the four corners of this pulse are precisely calculated using the helicopter's location at that instant as the center point of the rectangle. The area inside the four corners is referred to as the *footprint*.
- The exact position of each randomly laid mine is then checked to see if its position is within the footprint. If the footprint contains no mines, no further action occurs until the next 0.375 seconds have passed. At that time it emits a new pulse, identifying a new footprint (step 1.).
- If a mine *is* determined to be within the footprint, its depth is checked, and its lateral range from the center of the footprint is calculated. With depth and lateral range, the appropriate probability of detection value, $\mathbf{P}_{d(i,j)}$, can then be applied.
- A Uniform[0, 1] random number is generated and compared to $\mathbf{P}_{d(i,j)}$ using the following sequence:

```
IF Pd(i,j) > Random Number ~ U[0,1]
        THEN Detected = TRUE;
ELSE
        Detected = FALSE;
END
```

At the end of each replication, the total number of mines detected in each depth zone is displayed to the user as well as the number of mines that were missed. When all replications have been completed, a separate graph is presented for each depth zone, showing performance statistics for the search. Figure 9 is an example of a typical graph presented for one depth zone. The graph shows the number of mines detected in each replication of the search plan as well as the running average of mines detected, recalculated after each replication.

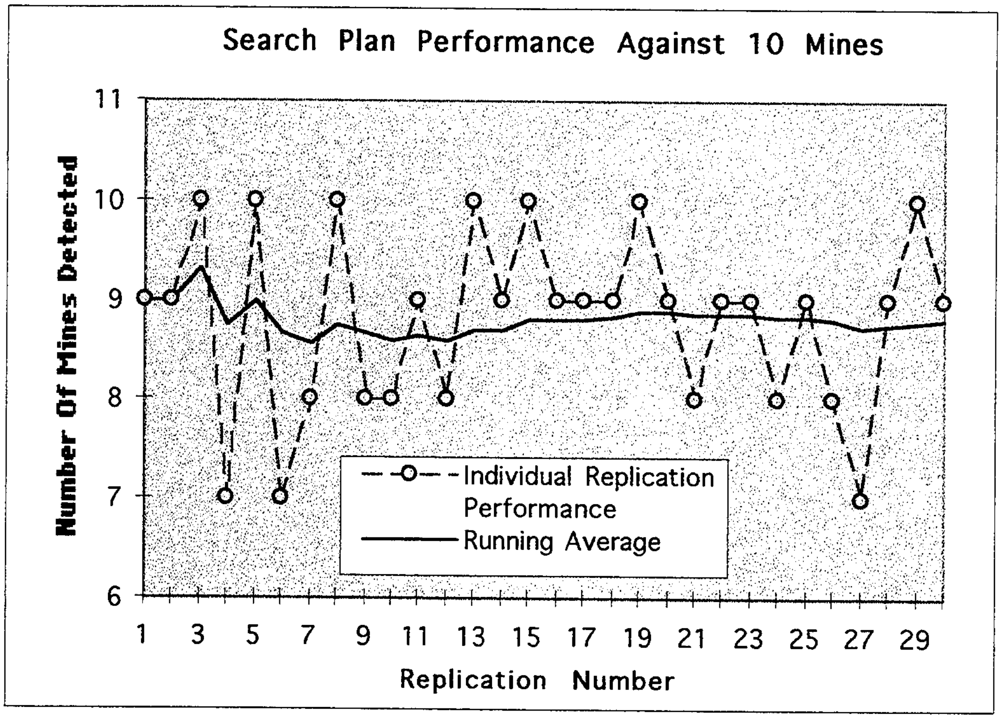


Figure 9. Performance Statistics

After the four performance graphs are displayed, the user is given the choice of viewing an animated iteration of his search plan, selecting a different number of tracks to be replicated, or terminating the program.

D. ANIMATION

The animation of the search plan is an opportunity for the planner to assess whether the number of tracks selected in his plan is sufficient (see Figure 6). The performance statistics that he has received at this point give him the final results, but they do not distinguish between mines missed because of poor sensor performance and mines missed because of holidays in the search plan. Analytical planning models do not make this distinction either since they generally provide expected coverage percentage, but do not address the likelihood that a mine is located within a holiday.

A mine that is located inside of a holiday cannot be detected because it is never within the search volume of the sensor. Thorough searches generally do not include holidays because the tracks are numerous enough to make up for navigational errors. However, if the planner is under time constraints, he may not have the luxury of saturating the channel with additional tracks. In these instances, an animated sample of his plan may convince him to adjust the size of the channel or request additional assets.

The user is reminded that the animation is simply one iteration of the search plan, and that it does not represent an exact prediction for the performance of the search. Nevertheless, by running the animation, if he sees large and numerous holidays, he should be persuaded to add tracks for better coverage.

E. KEY MODEL ASSUMPTION

The primary assumption in ML-Recon is that each attempt to detect a mine is independent. There is no environmental phenomenon or shortcoming in the sensor that makes some mines harder to detect. As long as a mine is flown over by the helicopter and is within the depth capabilities of the sensor, it has the potential to be detected.

IV. THE EXPERIMENT

A. OVERVIEW

A verification test for any simulation model is performed to show that the program behaves as intended, checking that the conceptual model (e.g. flowcharts and assumptions) is translated into a correctly working computer program. Validation of a simulation is performed by showing that the conceptual model is accurate [Ref. 9].

Verification for ML-Recon is carried out by comparing it to an accredited model currently used in the fleet by MCM planners. Further analysis is conducted on ML-Recon alone. This is done to explain the particular features of the simulation that make it preferable to an analytical model as a planning aid.

In order to validate ML-Recon, it must be compared to results of field tests separate from those used in building the model. This is left as future work as data for such tests are not available at the submission of this thesis.

B. ML-RECON VS. UCPLN

The Uniform Coverage Plan (UCPLN) is an interactive computer program currently used by MCM planners in the fleet [Ref. 6]. The model uses analytical methods to calculate percent clearance achievable in a potentially mined channel. Inputs to UCPLN that are also required in ML-Recon are:

- area length and width;
- navigational error;
- percent clearance desired;
- speed
- sensor sweep width, and;

To compare ML-Recon to UCPLN, some modifications to the code are required. For sensor sweep width ML-Recon uses a lateral range function with five different $\mathbf{P}_d$ values in each of four depth zones. The UCPLN program uses a single value for $\mathbf{P}_d$ across the entire sweep width of the sensor. Therefore, for the experiment, the $\mathbf{P}_d$ across the lateral range is aggregated in ML-Recon to one value for each depth zone. Rather than further aggregate the $\mathbf{P}_d$, each depth zone is run separately.

The test scenarios are search plans consisting of 5 through 16, 32, 48 and 64 tracks. Channel-size is kept constant throughout the experiment, and chosen so that five tracks would provide poor coverage, and 64 tracks would provide nearly complete

coverage. One hundred replications of ML-Recon were run for each search plan. Results are compared to UCPLN values achieved with the same input parameters.

V. EXPERIMENTAL RESULTS

A. OVERVIEW

The analysis of the first experiment is presented with a higher level of detail since the values used for $\mathbf{P_d}$ of the sensor and for the dimensions of the laser footprint are notional. The subsequent analysis, using the real values, is presented in a way that is clear after the notional case is explained, but which does not reveal any classified information. The final analysis is done on ML-Recon alone, using notional numbers to describe how to attain the most useful results when planning a search.

B. ML-RECON VS. UCPLN (Notional Values)

In addition to the similarity in results between ML-Recon and UCPLN, the stochastic nature of ML-Recon is evident against the analytical results of UCPLN in Figure 10. The graph is taken from one depth zone with a notional $\mathbf{P_d}$ of 0.5.

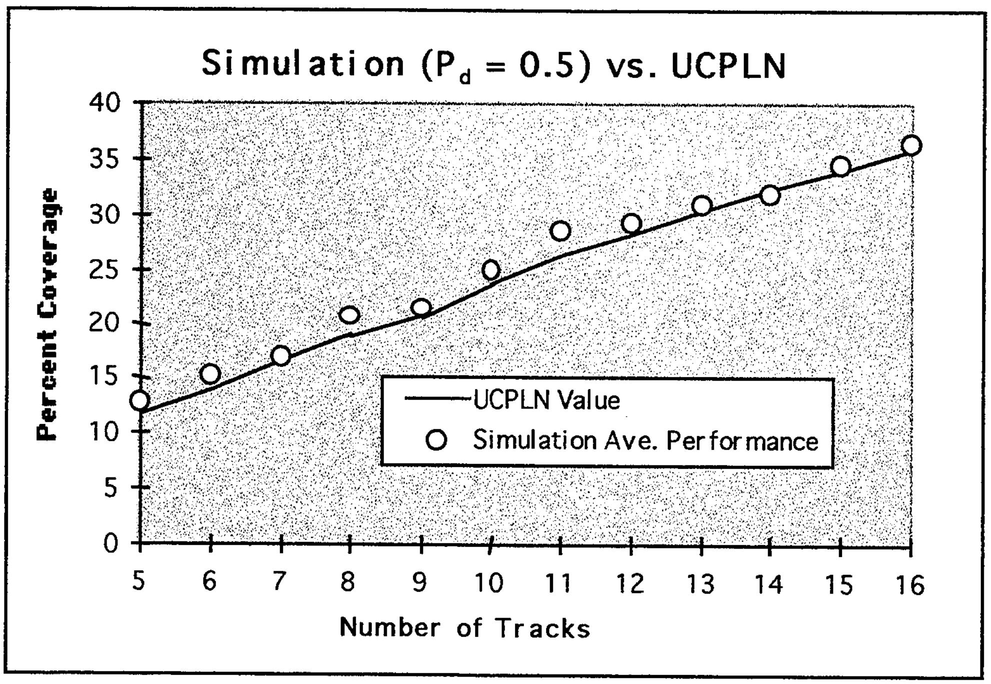


Figure 10. ML-Recon Results vs. UCPLN

The following analysis is conducted in order to determine whether or not the average performance generated by 100 replications of ML-Recon is equivalent to the

analytically derived, predicted performance from UCPLN for the same search plan. In the analysis the following symbols are used:

$\boldsymbol{i}$ - depth zone index; $\boldsymbol{i} = 1, 2, 3, 4$;
$\boldsymbol{n}$ - number of replications requested by the user;
$\boldsymbol{r}$ - replication number index; $\boldsymbol{r} = 1, 2, \ldots, \boldsymbol{n}$;
$\boldsymbol{x}_{i,UCPLN}$ - analytically derived percentage of mines detected with UCPLN in depth zone $\boldsymbol{i}$;
$\boldsymbol{x}_{i,1}, \boldsymbol{x}_{i,2}, \ldots, \boldsymbol{x}_{i,r}$ - random sample of size r of the percentage of mines detected in ML-Recon in depth zone $\boldsymbol{i}$, with mean μ_i and variance σ_i^2.

The average performance of the simulation for any particular depth zone, $\boldsymbol{i}$, over $\boldsymbol{n}$ replications is represented by the random variable, $\bar{x}_i$, where

$$\bar{x}_i = \frac{1}{n}\sum_{r=1}^{n} x_{i,r} \tag{7}$$

Using $\bar{x}_i$ as a large-sample estimator for $\boldsymbol{x}_{i,UCPLN}$, it is assumed that $\bar{x}_i$ has a distribution that is approximately normal with mean $\mu_{\bar{x}_i} = \mu_i$ and variance $\sigma_i^2/\sqrt{\mathbf{n}}$ [Ref. 10]. Since the UCPLN program is accredited and in use in the fleet, $\boldsymbol{x}_{i,UCPLN}$ is the value against which ML-Recon's average performance is tested. The null and alternate hypotheses for this test are then:

$$\mathrm{H}_0 : \bar{x}_i = x_{i,UCPLN} \qquad \text{against} \qquad \mathrm{H}_a : \bar{x}_i \neq x_{i,UCPLN}$$

The test statistic, $\boldsymbol{z}_i$, is determined by

$$z_i = \frac{\bar{x}_i - x_{i,UCPLN}}{\sigma_{\bar{x}_i}} = \frac{\bar{x}_i - x_{i,UCPLN}}{\sigma_i / \sqrt{n}} \tag{8}$$

The actual variance, σ_i^2, of $\boldsymbol{x}_{i,r}$ is not known but can be estimated (because $\boldsymbol{n} = 100$, used in the test, is sufficiently large [Ref. 10]) by the observed variance, s_i^2, where

$$s_i^2 = \frac{\sum_{r=1}^{n}(x_{r,i} - \bar{x}_i)^2}{n-1} \tag{9}$$

The observed value of the test statistic for each search tested is given for each depth, i, by

$$z_i = \frac{x_i - x_{i,UCPLN}}{s_i / \sqrt{n}} \tag{10}$$

Table 1 shows the values achieved by ML-Recon and UCPLN for a depth zone with an aggregate (notional) $\mathbf{P_d}$ of 0.5. It also shows the difference between the two and the **z** test statistic for each search plan. Acceptance or rejection of the null hypothesis is based on a two-tailed **z**-test using an α of 0.05. As the table shows, only two rejections were observed out of the 15 comparisons conducted in this experiment.

Tracks	UCPLN	ML-Recon	Difference	ML-R STDEV	z stat	Accept/Reject
5	11.73	12.68	0.95	6.41	1.48	Accept
6	13.9	15.2	1.3	7.8	1.67	Accept
7	16.44	16.76	0.32	6.84	0.47	Accept
8	18.9	20.6	1.7	8.8	1.93	Accept
9	20.51	21.28	0.77	8.22	0.94	Accept
10	23.61	25	1.39	8.85	1.57	Accept
11	26.36	28.48	2.12	8.66	2.45	Reject
12	28.38	29.32	0.94	9.45	0.99	Accept
13	30.34	30.88	0.54	9.34	0.58	Accept
14	32.25	31.84	-0.41	8.64	-0.47	Accept
15	34.11	34.4	0.29	9.27	0.31	Accept
16	35.91	36.44	0.53	7.34	0.72	Accept
32	58.9	58.88	-0.02	8.61	-0.02	Accept
48	73.62	69.48	-4.14	8.89	-4.66	Reject
64	83.04	82.88	-0.16	7.67	-0.21	Accept

Table 1. ML-Recon vs. UCPLN Results (Notional Values).

C. ML-RECON VS. UCPLN (Actual Values)

The same two-tailed **z**-test was conducted to compare ML-Recon's average results to UCPLN using the $\mathbf{P_d}$ values determined in the operational tests of Magic Lantern. The results shown in Table 2 are from a comparison of the third depth zone (Z3) to the UCPLN-generated value for the number of mines detected in each search plan. Although the actual performance of ML-Recon is omitted for classification reasons, the other statistics, as described in the notional case, are included. Results for the other three depth zones are similarly presented in Appendix B. As in the notional case, the number of rejections at each depth zone is two, although they do not occur for the same number of tracks in each case.

Tracks	UCPLN - MLRecon	ML-R STDEV	z statistic	Accept/Reject
5	-0.22	9.97	-0.22	Accept
6	0.62	10.19	0.61	Accept
7	0.21	8.75	0.24	Accept
8	1.22	11.55	1.06	Accept
9	1.64	10.26	1.60	Accept
10	-1.81	9.19	-1.97	Reject
11	-0.58	9.09	-0.64	Accept
12	-0.22	10.81	-0.20	Accept
13	-0.13	8.98	-0.14	Accept
14	-1.53	9.09	-1.68	Accept
15	-0.78	7.45	-1.05	Accept
16	0.46	8.58	0.54	Accept
32	0.88	3.90	2.26	Reject
48	0.04	1.82	0.22	Accept
64	-0.07	0.95	-0.73	Accept

Table 2. ML-Recon vs. UCPLN (Actual Values).

D. MINE DENSITY'S AFFECT ON PERFORMANCE VARIABILITY

The Monte Carlo approach to formulating a sea mine reconnaissance plan provides the user with more information than just the expected average performance of the Magic Lantern system. The requirement for the user to enter the number of mines in the channel was mentioned in the description of the model. Figure 9 shows an example of a typical performance graph displayed to the user when the replications have been completed. In that graph, as the number of replications increases, the running average becomes more flat. This indicates that the best estimate for the average number of mines detected with that particular search plan in that depth zone is achieved by running as many replications as practical. The individual results of each search on the graph shows the planner how much worse than the average his plan *may* perform. This variation in results depends on the number of mines entered by the user at the beginning of the program.

The reason for this direct relationship between variance and the number of mines in the channel is that the number of mines detected in each depth zone on any replication, for the purposes of this analysis, is approximated by a binomial distribution. This is illustrated by equating ML-Recon to the definition of a binomial experiment [Ref. 10].

- The experiment consists of $\boldsymbol{m}$ identical trials, or detectable mines in any particular depth zone.
- Each trial results in success or failure with probability $\boldsymbol{p}$, or, each mine is detected with probability $\mathbf{P_d}$ in each depth zone and lateral range.
- The trials are assumed to be independent, as each mine that is flown over has the same chance of being detected as any other mine, regardless of whether others have been detected or not.*
- The random variable, $\boldsymbol{x_i}$, represents the number of mines detected out of the $\boldsymbol{m}$ total mines in any given depth zone, $\boldsymbol{i}$.

Having identified the distribution of the number of mines detected in any depth zone as approximately binomial, the relationship between the number of mines in the channel to begin with and the variance in the number detected can be explained using the following notation:

$\boldsymbol{m}$ = number of mines in each depth zone;

$\boldsymbol{p_i}$ = aggregate probability of detecting any mine in depth zone $\boldsymbol{i}$;

$\boldsymbol{x_i}$ = no. of mines detected in depth zone $\boldsymbol{i}$ for a given search plan; $\boldsymbol{x_i} \sim \text{Bin}(\boldsymbol{m}, \boldsymbol{p_i})$;

Since $\boldsymbol{x_i}$ is assumed to follow a binomial distribution,

$$\mathrm{E}[\boldsymbol{x_i}] \equiv \boldsymbol{m p_i} \tag{11}$$

and

$$\mathrm{E}[\boldsymbol{x_i}/\boldsymbol{m}] \equiv \boldsymbol{p_i} \tag{12}$$

Here it is clear that, by increasing the number of mines in the channel, the expected fraction of mines detected does not change, since $\boldsymbol{p_i}$ is constant. Therefore, the number of mines does not affect the average performance of the search plan. However, the variance equation for the fraction of mines detected shows that, as **m** increases, the variance of the fraction of mines detected decreases.

$$\mathrm{Var}[\boldsymbol{x_i}/\boldsymbol{m}] = 1/\boldsymbol{m}^2\,\mathrm{Var}[\boldsymbol{x_i}] \equiv \boldsymbol{p_i}(1 - \boldsymbol{p_i})/\boldsymbol{m} \tag{13}$$

* It should be noted that, in reality, there is a very slight dependence between trials. Since there is a random cross-track in error in the helicopter's flight path, consider the unlikely case in which every track of the plan is actually flown outside of the channel. None of the mines would have a chance of being detected, they all are share the same flawed search path, and their chances of being detected are, therefore, not independent. However, since such a case, or any one like it, is so unlikely, the independence assumption is made.

Therefore, by increasing the number of mines in the channel, the spread in the results is reduced, although the average remains the same.

Figure 11 gives a visual sample of this phenomenon. In both of the graphs shown, 40 tracks were run for 30 replications, and the sensor's probability of detecting a mine was 0.5. The size of the channel in each case was the same. The difference in the two is that the one on the left is for a channel with 10 mines, and the one on the right is for a channel with 100 mines. The average fraction of mines detected in each plan, x_i/m, is

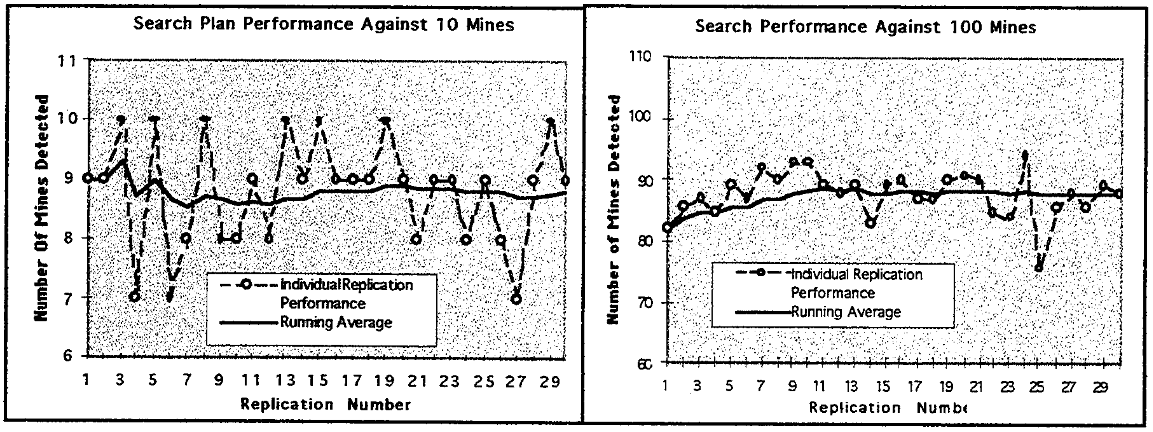


Figure 11. Results From Channel With 10 Mines and Channel With 100 Mines.

approximately equal (i.e. 8.8/10 ≈ 87.8/100). However, the standard deviation of x_i/m is substantially smaller in the graph on the right:

$$\frac{3.64}{100} < \frac{0.92}{10} \tag{14}$$

This is attributable to the binomial nature of x_i.

The possibility also exists that the planner is interested in the actual number of mines remaining *undetected* in the channel after the search is complete, regardless of the fraction of mines detected. ML-Recon accommodates this approach by printing the number of undetected mines after each replication.

VI. CONCLUSION

The simulation presented in this thesis, ML-Recon, meets the MCM planner's requirements for a planning tool that accurately represents a conceptual model of the Magic Lantern system. It provides him with the information that is essential to formulating an efficient and thorough search plan.

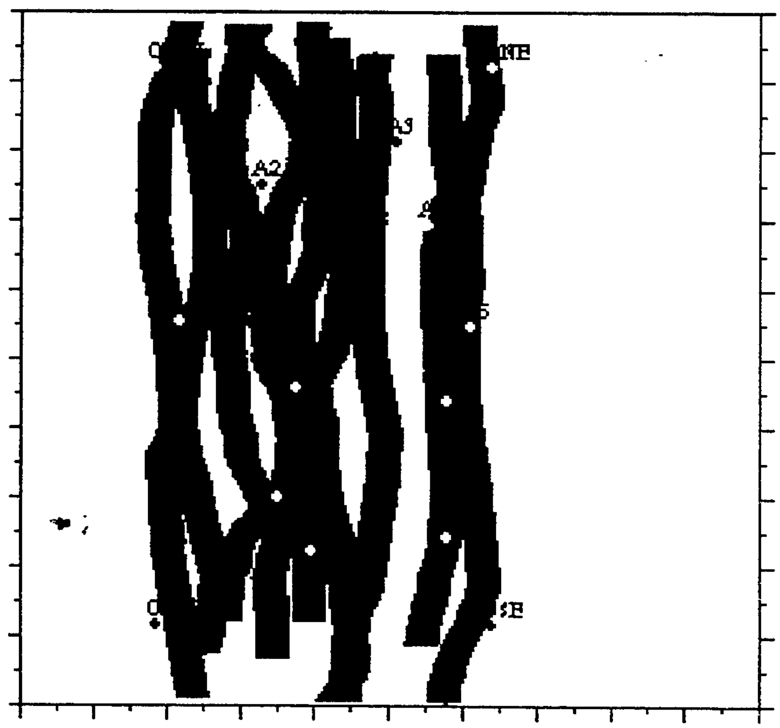
ML-Recon's stochastic treatment of the helicopter's cross-track error is a unique feature that gives the planner insight toward the likelihood of holidays in his plan. The stochastic representation of the sensor also contributes to a *spread* of realistic results based on many replications. By using this model prior to deploying the system, he can be confident that his plan is thorough enough that all potential mines will at least be flown over, yet not so ambitious that it will have to be terminated prematurely to refuel the helicopter.

Should there be improvements to the Magic Lantern system, or if it is adapted to a different helicopter, the model can continue to meet the planner's needs by simply replacing the applicable descriptive parameters.

APPENDIX A. MAGIC LANTERN HELICOPTER PLOT

The figure below is a record of a helicopter's actual tracks during Magic Lantern field tests conducted in July, 1994. The units for the x and y axes are omitted for security reasons. The intent of this graphic is to illustrate the error in the helicopter's flight path. The search plan for this sortie was a set of straight, uniformly-spaced tracks.

Metron Coverage Program (1994)



APPENDIX B. ML-RECON COMPARED TO UCPLN

Tracks	UCPLN-MLRecon	ML-R STDEV	z stat	Accept/Reject
5	-0.22	8.40	-0.26	Accept
6	-0.72	9.07	-0.79	Accept
7	2.06	10.45	1.97	Reject
8	1.65	9.85	1.68	Accept
9	0.9	10.40	0.87	Accept
10	3.4	11.99	2.84	Reject
11	-0.23	9.86	-0.23	Accept
12	1	10.15	0.98	Accept
13	-0.56	9.43	-0.59	Accept
14	-0.25	8.29	-0.30	Accept
15	0.12	8.68	0.14	Accept
16	1.52	9.01	1.69	Accept
32	0.67	4.96	1.35	Accept
48	-0.4	2.17	-1.85	Accept
64	-0.14	1.33	-1.05	Accept

Table 3. ML-Recon vs. UCPLN (Actual Values) For First Depth Zone (Z1).

Tracks	UCPLN-MLRecon	ML-R STDEV	z stat	Accept/Reject
5	-1.65	7.89	-2.09	Reject
6	-0.34	7.75	-0.44	Accept
7	0.09	8.88	0.10	Accept
8	-0.01	9.75	-0.01	Accept
9	-1.81	9.01	-2.01	Reject
10	1.54	8.17	1.88	Accept
11	-0.85	10.32	-0.82	Accept
12	0.57	9.16	0.62	Accept
13	-0.11	10.19	-0.11	Accept
14	0.36	8.76	0.41	Accept
15	-0.38	10.03	-0.38	Accept
16	-0.8	10.65	-0.75	Accept
32	-0.14	7.63	-0.18	Accept
48	0.06	5.80	0.10	Accept
64	0.45	4.31	1.04	Accept

Table 4. ML-Recon vs. UCPLN (Actual Values) For Second Depth Zone (Z2).

Tracks	UCPLN-MLRecon	ML-R STDEV	z stat	Accept/Reject
5	0.26	8.74	0.30	Accept
6	-0.18	10.78	-0.17	Accept
7	0.69	9.56	0.72	Accept
8	-0.22	9.55	-0.23	Accept
9	-0.23	8.83	-0.26	Accept
10	2.91	13.74	2.12	Reject
11	-2.07	9.53	-2.17	Reject
12	-0.76	8.05	-0.94	Accept
13	1.55	8.99	1.72	Accept
14	-0.75	8.58	-0.87	Accept
15	0.97	9.07	1.07	Accept
16	-0.54	8.99	-0.60	Accept
32	-0.03	4.62	-0.06	Accept
48	0.24	2.68	0.90	Accept
64	-0.1	1.45	-0.69	Accept

Table 5. ML-Recon vs. UCPLN (Actual Values) For Fourth Depth Zone (Z4).

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9.	METRON, Inc. ATTN: Dr. H.R. Richardson 11911 Freedom Drive Suite 800 Reston, VA 22090-5602	2

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